"Novel Soft Computing Methods for Classification and Rule Extraction"

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Abstract of proposed work plan/problem:

In the present era, explainable accurate predictions are very much needed to enhance quality, performance and reduce losses. Prediction is essentials in almost every area such as medical, business, whether-forecasting, e-marketing, security and many more. Accurate predication requires processing of large amount of data and identify common properties and classify them into different classes. Pattern recognition and pattern classification helps in identifying hidden patterns in data and categorize them.

The domain of pattern classification (PC) has been an active research area for many decades. Use of Computational Intelligence (CI) models such as Artificial Neural Networks (ANN), data mining techniques etc. are becoming common in pattern classification and recognition systems. Through neural network have achieved highest accuracy in classification problem with large data, the obtained results are hard to interpret as they are often considered as black-box. To overcome this problem, significant research is going on for development of rule extraction algorithms that dissolve the black box nature of neural networks. Rule extraction is the process of developing natural language like syntax to describe the behavior of neural network system. There are methodologies available for rule extraction in pattern recognition and classification.

Recent trend is growing towards developing pattern recognition and classification systems using novel methods of soft computing tools. Our work aims at designing of novel methods for classification and rule extraction using soft computing tools.

1. Introduction:

Accurate prediction in business and marketing, correct diagnosis in medical and perfect recognition in security field helps to improve performance, enhance quality and avoid losses. A very promising tool to achieve this objective is the use of data mining.

There are several data mining techniques, such as clustering, classification, and outlier detection. Among these, classification is one of the most frequently studied techniques. Classification is a process of supervised learning where data is separated into different classes. Classification maps data into predefined groups of classes. The goal of a classification model is to predict the target class for each sample in the dataset. One the powerful approach for classification of data is ANN.

ANN are biologically inspired network, it imitates the behaviour of human brain to solve and draw conclusions in complex problems such as recognition of face, voice, and iris and so on. It is also useful for diagnosis of various diseases like cancer, heart and many more. Accurate prediction using ANN enables improvement in performance and enhancement in quality.

Neural networks and fuzzy set theory, which are termed soft computing techniques, are tools of establishing intelligent systems. A fuzzy inference system (FIS) employing fuzzy if-then rules in acquiring knowledge from human experts can deal with imprecise and vague problems [3]. FISs have been widely used in many applications including optimization, control, and system identification. Fuzzy systems do not usually learn and adjust themselves [4], whereas a neural network (NN) has the capacity to learn from its environment, self-organize, and adapt in an interactive way. For these reasons, a neuro-fuzzy system, which is the combination of fuzzy inference system and neural network, has been introduced to produce a complete fuzzy-rule-based system [5, 6]. The merits of neural networks and fuzzy systems can be integrated in a neuro-fuzzy approach. Fundamentally, a neuro-fuzzy system is a fuzzy network that not only includes a fuzzy inference system but can also overcome some limitations of neural networks, as well as the limits of fuzzy systems [7, 8] because it can learn and represent knowledge in an interpretable manner and learning ability. One of the neuro-fuzzy systems, a neuro-fuzzy classifier (NFC), combines the powerful description of FIS with the learning capabilities of NNs to partition a feature space into classes. NFCs have been commonly used for different problems [9,10].

2. Soft computing tools:

Soft Computing is an evolving collection of artificial intelligence methodologies aiming to exploit the tolerance for imprecision and uncertainty that is inherent in human thinking and in real life problems, to deliver robust, efficient and optimal solutions and to further explore and capture the available design knowledge. Soft computing utilizes computation, reasoning and inference to reduce computational cost by exploiting tolerance for imprecision, uncertainty, partial truth and approximation.

Soft Computing with its roots in fuzzy logic, artificial neural network, and evolutionary computation has become one of the most important research field applied to numerous engineering areas such as Aircraft, Communication networks, computer science, power systems and control applications.

Soft Computing Techniques comprises of core methodologies: Fuzzy Systems (FS), including Fuzzy Logic (FL); Evolutionary Computation (EC), including Genetic Algorithms (GAs); Artificial Neural Networks (ANN), including Neural Computing (NC); Machine Learning (ML); and Probabilistic Reasoning (PR). Where PR and FL systems are based on knowledge-driven reasoning, whereas, ANN and EC, are data-driven search and optimization approaches.

i. Artificial Neural Networks:

The concept of ANN has been inspired by biological neural networks. Biological neural networks have the following features:

- They are highly parallel, robust and fault tolerant nonlinear devices.
- They have built-in capability to adapt their synaptic weights to changes in the surrounding environment.
- They can easily deal with imprecise, fuzzy, noisy and probabilistic information.
- They can generalize from known tasks or examples to unknown ones.

One of the main motivations of ANN is to design problem solving devices incorporating some or all of these characteristics. The purpose of ANN is to use principles from nervous systems to solve complex problem in an efficient manner. The neuro-computing paradigm is different from programmed instruction sequence. Here information is stored in the synaptic connections, not in the main memory. A neuron is an elementary processor with primitive types of operations, like summing the weighted inputs coming to it and then amplifying or thresholding the sum.

In a classification or prediction problem, ANNs are used as a tool to analyze datasets. A multilayer feed-forward network is an important class of neural networks [5].

The ANN is composed of richly interconnected non-linear nodes that do processing in parallel. The connection weights are modifiable, allowing ANN to learn directly from examples without requiring or providing an analytical solution to the problem. The most popular forms of learning are [6]:

Supervised learning: Patterns for which both their inputs and outputs are known are presented to the ANN. The task of the supervised learning is to predict the value of the function for any valid input object after having seen a number of training examples. ANN employing supervised learning has been widely utilized for the solution of function approximation and classification problems.

Unsupervised learning: Patterns are presented to the ANN in the form of feature values. It is distinguished from supervised learning by the fact that there is no a priori output. ANN employing unsupervised learning has been successfully employed for data mining and clustering tasks. The self-organizing map (SOM) and adaptive resonance theory (ART)

constitutes the most popular examples of this class.
A back-propagation network (BPN) uses a supervised learning method and feed-forward architecture. It is one of the most frequently utilized neural network techniques for classification and prediction and is considered as advanced multiple regression analysis that can accommodate complex and non-linear data relationships [6].

ii. Fuzzy Logic systems:

Fuzzy sets were a new way to represent vagueness in everyday life. They attempt to model human reasoning/thinking process. Fuzzy sets are generalization of crisp sets and have greater flexibility to capture faithfully various aspects of incompleteness or imperfection in information. For an ordinary set, an element either belongs to it or not; while for fuzzy sets, an element can partially belong to the set; for example, a set of TALL persons. Here there is no precise boundary to the set TALL, and therefore, we cannot really isolate a collection of people labeled as tall. Fuzzy sets are conceptual sets, whose semantic is more important than its mathematical characterization. Mathematically, a fuzzy set is nothing but a mapping (known as membership function) from the universe of discourse $X\ to$ $[0,1]$.
Since fuzzy sets characterize imprecise properties, they can be effectively used to model vagueness associated with real-life systems. Fuzzy logic is based on the theory of fuzzy sets and approximate reasoning. It is much closer in spirit to human reasoning and natural language than the traditional logical system. Thus, fuzzy logic provides an effective means to model faithfully the approximate and inexact nature of the real world [3].

iii. Genetic Algorithms:

Genetic algorithms (GAs) are another biologically inspired computing tool for optimization. GAs are parallel and randomized search techniques, where a population of solutions evolves over a sequence of generations to possibly a globally optimal solution. Based on a fitness function good solutions are selected for reproduction using two genetic recombination operators: crossover and mutation. GAs are optimization algorithms which can solve problems resistant to other known optimization methods. They do not require differentiability or continuity of the fitness function. However, if the fitness function is differentiable then this information can be exploited to expedite searching by GAs. Even if the fitness function is not mathematically well structured, they can be used to find an optimal solution. Unlike conventional search techniques, GAs work simultaneously on multiple points in the search space, not on a single point. Due to the stochastic characteristic, they have a low chance of getting stuck to a local minimum. Good search algorithms should have the capability of both exploitation and exploration. GAs are believed to support a balanced mixture of both these features. The criterion of "survival of the fittest" provides evolutionary pressure for populations to grow with increasingly fit individuals and thereby exploits good solutions while the crossover and mutation operations enable GAs to explore the entire search space. There are many variants of GAs (conventional GAs), but the basic mechanism consists of the following steps:

1. Start with an initial population (a set of strings/ chromosomes).
2. Evaluate fitness of every string and select candidate strings with probability proportional to fitness value to form the mating pool.
3. Perform crossover and mutation.
4. Repeat steps 2 and 3 until the system ceases to improve, or some stopping criterion is reached.

3. **Review of Literature and Development in the subject (Previous work done in the revelant area):**
   - Anas Quteishat et al (2010) [10], have proposed a two stage PC and rule extraction system. The first stage consists of a modified fuzzy min–max (FMM) neural-network-based pattern classifier, while the second stage consists of a genetic-algorithm (GA)-based rule extractor called as FMM-GA. Main features of FMM-GA are the comprehensibility of the extracted rules and their compactness. They have evaluated its performance using five benchmark problems and a real medical diagnosis task. The results have been compared with those from FMM and pruned FMM, as well as other methods published in the literature. The outcomes confirms that the classification performances of proposed FMM-GA are better than those from other systems.
   - Mohammadi et al (2010)[71], proposed Fuzzy Hyper Sphere Neural Network (FHSNN), a supervised neural network, which utilizes fuzzy sets as pattern classes for detection of heart diseases. A class fuzzy set in FHSNN is a union of fuzzy set hyper spheres from the same class. In this work, two standard heart databases from machine learning UCI repository has been selected for the experimentation, which are SPECTF, STATLOG (Heart) databases. Training time is slightly more but, it needs to be trained only once so it can't be treated as a serious drawback. FHSNN is having capability to learn the patterns on fly makes it as a distinguished classifier from others. Its learning algorithm is simpler, easy to understand and can be parallelized easily.
   - Gallant (1988) [4] proposed one of the first rule extraction techniques from neural network. He was working on connectionist expert systems. In this work, each ANN node is represented as a conceptual entity. The information concealed in ANN is extracted in this work.
   - R. Setiono et al (2002) [1] introduced a rule extraction technique that approximated the activation function at each hidden neuron using a three- or five- piece linear function.
   - Humar Kahramanli and Novruz Allahverdi (2009) [7] have presented the technique of mining the classification rules for Liver Disorders using adaptive activation function. In this study the authors have first trained the neural network with adaptive activation function. Then the rules are extracted from this trained neural network by using the OptaiNET that is an Artificial Immune Algorithm (AIS). In this paper for rule extraction first, ANN which classifies the dataset was designed and then OptaiNET algorithm was executed for extraction of rules from this ANN. Finally the extracted rules were decoded. Produced rules diagnosed correctly 192 samples from 200 belong to Class 1 and 135 samples from 145 belongs to Class 2. It means system achieve 96% and 93% correctly diagnosis for Class 1 and Class 2 respectively. In summary the system correctly diagnosed 94.8% of whole samples.
   - L. Wang and J. Yen (1999) [8] Proposed GA based solution for rule exploration and extraction. Here GAs were used to select a small number of significant rules from a large pool of generated rules.
   - Oliver Nelles et al (1996) [9] propose a new method for fuzzy rule extraction from data by a genetic algorithm and a fine tuning of the extracted membership functions by a constrained nonlinear optimization. This approach is able to select the most significant rules out of a set of all possible ones that is it learns the rule structure by itself.
   - C. F. F. Carraro et al (2013) [11] proposed an extension to fuzzy rule extraction method from trained SVM (FREx-SVM) to improve classification performance. Here, the fuzzy sets are automatically tuned so to attain better classification performance without reducing the interpretability of the extracted fuzzy rules. FREx_SVM, was previously developed, providing rules with good accuracy and coverage of the database but the classification performance of the extracted rules was usually much lower than the original SVMs.

- Huysmans J. et al (2008) [44] presented Minerva, which is a new algorithm for rule extraction. The main advantage of Minerva is its ability to extract a set of rules from any type of black-box model.
- Setiono R. et al (2008) [43] presented a recursive algorithm for extracting classification rules from feedforward neural networks (NNs) that have been trained on data sets having both discrete and continuous attributes. The novelty of this algorithm lies in the conditions of the extracted rules: the rule conditions involving discrete attributes are disjoint from those involving continuous attributes.
- Schmitt E. et al (2008) [42] proposed an iterative method to select suitable features in an industrial pattern recognition context. It combines a global method of feature selection and a fuzzy linguistic rule classifier. It is applied to an industrial fabric textile context.
- Wentao Huang et al (2008) [41], in order to extract simple and certain diagnostic rules for wear pattern recognition of diesel engine from incomplete data, a method is proposed to directly extract decision rulesfor fault diagnosis.
- Meng Tang, and Koch W.H. (2009) [40] have constructed an intelligent model with fuzzy TS dynamic nonlinear autoregressive with exogenous input (NARX) is introduced for process state identification and behavior prediction for complex processes. In the model, fuzzy neural networks (FNNs) are applied as process state classifiers for process state (fault) detection. It indicates that the model has good performance for process state classification, identification and process behaviors prediction, as well as business rules extraction for making decision.
- Stavrakoudis D.G. and Theocharis J.B. (2009) [39] proposed the use of a boosted genetic fuzzy classifier (BGFC) for land cover classification from multispectral images. The model's learning algorithm is divided into two stages. The first stage iteratively generates fuzzy rules, employing a boosting algorithm that localizes new rules in uncovered subspaces of the feature space. The second stage fine-tunes the obtained rule base through an evolutionary algorithm (EA), improving the cooperation among the fuzzy rules and, thus, increasing the classification performance attained after the first stage.
- Tian Yu et al (2010) [38] conducted the research on the application of artificial neural networks in classification of data mining. Since the knowledge captured by neural networks is represented at a sub-symbolic level in terms of connections and weights, the paper aims at not only designing an artificial neural network prediction model for the time of delay payment but also extracting fuzzy production rules, a humanly understandable representation for neural networks.
- Luengo J. and Herrera F. (2010) [37] presented an automatic extraction method to determine the domains of competence of fuzzy rule based classification systems.
- Liu Wenjun and You Fei (2010) [36] have classified the objects in continuous domain decision table according to fuzzy clustering. Then, combined rough set theory with fuzzy set theory, an attribute reduct algorithm of decision table with continuous attributes was put forward. At last, a rule extraction algorithm was proposed and also the validity of this algorithm was accounted for through an example.
- Stavrakoudis D.G. et al (2011) [35] proposed a novel hierarchical genetic fuzzy rule based classification system (HGFRBCS), targeted at effectively handling high-dimensional classification tasks.
- Nguyen M.N. et al (2011) [34] used approach that has produced sets of comprehensible, and often interpretable, rules underlying the protein secondary structure (PSS) predictions. Moreover, many of therules seem to be strongly supported by biological evidence.
- Qiong Wu, and Xin Pan (2011) [33] proposed a novel classification method based on rough set theory that improved the rules matching mechanism.

- Si Xiao Yang and Ying Jie Tian (2011) [32] introduced a new method to extract knowledge with a thought inspired by the decision tree algorithm and give a formula to find the optimal attributes for rule extraction.
- Olmo J.L. et al (2011) [31] presented an ant programming (AP) framework, which is capable of mining classification rules easily comprehensible by humans and therefore, capable of supporting expert domain decisions. The algorithm proposed, called grammar based ant programming (GBAP), is the first AP algorithm developed for the extraction of classification rules, and it is guided by a context-free grammar that ensures the creation of new valid individuals.
- Chorowski J. and Zurada J.M. (2011) [30] presented a novel eclectic approach to rule extraction from NNs, named local rule extraction (LORE), suited for multilayer perceptron networks with discrete (logical or categorical) inputs. The extracted rules mimic network behavior on the training set and relax this condition on the remaining input space.
- Saeki T. et al (2011) [29] have studied the process of reducing the decision matrix, finds several properties useful for the rule extraction, and proposes an effective algorithm for the extraction. The algorithm is implemented in a piece of software and a simulation experiment is conducted to compare the reduced time of the software base on the proposed algorithm with that of LEM2 software which is open to the public on the Internet, and is widely used throughout the world.
- Kasiri H. et al (2011) [28] executed a new genetic fuzzy system (GFS) successfully to extract rules from neural network (NN). fuzzy rule extraction from neural network using GA (FRENGA) recognizes disturbance wind in turbine input. Thus it generates desired pitch angle control. Consequently, output power has been regulated in the nominal range.
- Keem Siah Yap et al (2011) [27] proposed an improved Generalized adaptive resonance theory (GART) model (IGART), and demonstrate its applicability to power systems. IGART enhances the dynamics of GART in several aspects, which include the use of the Laplacian likelihood function, a new vigilance function, a new match-tracking mechanism, an ordering algorithm for determining the sequence of training data, and a rule extraction capability to elicit if-then rulesfrom the network. To assess the effectiveness of IGART and to compare its performances with those from other methods, three datasets that are related to power systems are employed.
- Watanabe T., and Fujioka R. (2012) [26] defined the equivalence redundancy of fuzzy items and related theorems as a new concept for fuzzy data mining. Then, proposed a basic algorithm based on the a priori algorithm for rule extraction utilizing the equivalence redundancy of the fuzzy items based on redundancy concepts of fuzzy association rules.
- Syose T. et al (2012) [25] conducted the rule extraction by fuzzy neural network (FNN) from the learning result of adaptive learning cerebellar model articulation controller (CMAC). By using this method, the extracted rule makes easy to understand for human. In addition, an operator's skill is acquired from the operators whose a level of skill is different.
- Hara A. and Hayashi Y. (2012) [24] proposed a feed-forward ensemble neural network for data sets having both discrete and continuous attributes. The ensemble provides results that are more accurate than those of conventional neural networks and expresses more comprehensible rules.
- Yi-Cheng Chen et al (2012) [23] presented an integrated mechanism for simultaneous extraction of fuzzy rules and selection of useful features. Since the feature selection method is integrated into the rule base formation, the scheme can account for possible subtle nonlinear interaction between features, as well as that between features

and the tool, and, consequently, can select a set of useful features for the classification job.

- Jianguo Wang et al (2012) [22] proposed a new rule extraction algorithm based on convex hull theory, in order to open the black-box. First, all the vectors were clustered to be some clusters on the decision hyper-plane then, extracted the convex hull for every cluster; finally, the region of each convex hull covered were transferred to each interval-type rule.
- Kianmehr K. (2012) [21] presented an adaptive classification framework for a realtime intrusion detection system that changes its behavior according to the patterns occurred in the new received data. The performance of the system is constantly monitored and whenever it drops under a certain level of accuracy, the classifier model is retrained to learn new patterns and eliminate the obsolete ones from its knowledge. Further, the framework uses a semi rule-based approach to classification in order to make the model more understandable for human experts and facilitate the user interference in the learning process.
- Sheng Liu et al (2012) [20] proposed an efficient algorithm, combined rule extraction and feature elimination (CRF), based on 1-norm regularized random forests. CRF simultaneously extracts a small number of rules generated by random forests and selects important features.
- Sethi K.K.et al (2012) [19] proposed a novel pedagogical rule extraction technique to generate a decision table using training example set and a trained artificial neural network on it. The proposed algorithm can be used with both discrete as well as continuous input. It has advantage in terms of computational performance and memory management.
- de Fortuny E.J. and Martens D. (2012) [18] presented a new pedagogical rule extraction algorithm for regression, based on active learning, which can be combined with any existing rule induction technique.
- Akhlagh M.M. et al (2012) [17] proposed temporal classifier. In this study, to make use of this temporal sequence, a procedure called temporalisation is applied to merge consecutive records. The learning algorithm is an entropy-based decision tree integrated with temporal decision tree concept. Furthermore, a probabilistic approach based on Bayes' theorem is applied to enhance prediction accuracy. The proposed temporal classifier is evaluated with three real datasets.
- Azcarraga A. Et al (2012) [16] explained how the backpropagation network works, a rule extraction method will be used to extract symbolic data from the resulting backpropagation network. The rules extracted can then be transformed into decision trees performing almost as accurate as the network plus the benefit of being in an easily comprehensible format.
- Jinsai Jiang et al (2013) [15] proposed a method to extract global fuzzy rules from distributed data in a privacy-preserving manner. This method transfers only values necessary for the extraction process without collecting any data at one place and can obtain the global fuzzy rules at all places.
- Chong Liu et al (2013) [14] described the method for classifying multiclass motor imagery EEG signals of brain-computer interfaces (BCIs) according to the phenomena of event-related desynchronization and synchronization (ERD/ERS). The method of one-versus-one common spatial pattern (CSP) for multiclass feature extraction was employed. And extended two different kinds of classifiers: 1) SVM based on maximal average decision value and 2) k-nearest neighbour (KNN) rule for multiclass classification.
- Surendran A. and Samuel P (2013) [13] proposed an approach based on a particular type of program slicing named partitioned forward slicing, which helps to identify the rules and logic spread over the code. The work dealt with the process of extracting rules and logic from business systems during the maintenance phase of

software development. The rules and logic thus extracted may be useful in re-engineering, re-use and reverse engineering.

- Olmo Juan Luis et al (2013) [12] presented an ant-based automatic programming method for discovering rare association rules. This algorithm lacks the drawbacks of exhaustive approaches, having also some advantages, such as the employment of a context-free grammar that allows to adapt the algorithm to a particular domain. Results show that this proposal can mine a set of reliable infrequent rules in a short period of time.
- Shinde S. V et al (2014) [52] proposed modified fuzzy hyperline segment neural network (MFHLSNN). In MHLSNN membership function is based on minimum of the distance of the input pattern from the midpoint of the hyperline segment and its distance from both the end points. The proposed model is applied to eight different benchmark datasets taken from the UCI machine learning repository. The experimental results of the MFHLSNN are compared with earlier methods like fuzzy min-max neural network, generalized fuzzy min-max neural network and fuzzy hyperline segment neural network. These results show that the MFHLSNN gives improved performance as compared to its earlier methods.
- Shinde S. V et al (2017) [53] In proposed Extended fuzzy hyperline segment neural network (EFHLSNN), each hyperline segment has two end points defined not only in terms of continuous attributes but also the set of binary strings defined for discrete attributes. The membership function and expansion condition of the original FHLSNN are modified to process both continuous and discrete attribute values. The proposed EFHLSNN model is applied to eight different benchmark datasets. The experimental results show that the proposed model gives very good accuracy and the compact rule set that justifies the classification decision of the EFHLSNN and thus, giving rise to good rule fidelity.
- Esteva, Andre, et al (2017) [56] demonstrated classification of skin lesions using a single convolutional neural network (CNN), trained end-to-end from images directly, using only pixels and disease labels as inputs. The CNN achieved performance on par with all tested experts by demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists.

4. **Objectives of Research/Proposed Hypothesis:**

Objective of research is to design state-of-art algorithms for extracting a set of compact yet easily comprehensible rules using soft computing tools. Using these rules high classification performance can be achieved in pattern classification task along with comprehensive explanation facility for classification.

5. **Methodology to be adopted:**

After thorough study of currently proposed methods and their implementation, new research direction will be determined. This involves designing novel algorithms. Then, these algorithms will be implemented using suitable tool such as MatLab, SkyLab or Weka. Results will be compared to best contemporary methods which will give more insight and useful directions for further progress of research work.

6. **Importance of study/Society application:**

- **National and International status:**

In the recent years, hybrid systems using models of CI, that include ANN, fuzzy Logic and GAs, have become popular for PC and rule extraction. Thus such systems combine the strengths of these three components. The literature in this area is very vast and growing. At national level, Kulkarni U. V. is one of researchers who works in this area

and has proposed few algorithms which can be used for classification and clustering of patterns [45-50]. Swati Shinde has worked on fuzzy hyperline segment for classification [52, 53] and used artificial neural network for mining rules [54, 55]. Jaishri M. Waghmare has proposed new methods for extraction of classification rules for FMN framework. Pal N. R. has worked on finding optimal rule base for classification and to select a set of useful features that may solve the classification problem. Also Pal N. R. with Laha A. and Das J. have proposed a multistage classifier that involves fuzzy rule extraction from the training data and then the generation of a possibilistic label vector for each pixel using the fuzzy rule base. To exploit the spatial correlation of land cover types, they proposed different information aggregation methods which use the possibilistic class label of a pixel and those of its eight spatial neighbours for making the final classification decision. R. Krishnan, G. Sivakumar and P. Bhattacharya presented an algorithm for rule extraction from feedforward neural networks with boolean inputs. At international level, many researchers have worked in this area. It is covered in the literature survey.

- **Significance of the study:**

  It is generally easy for a person to differentiate the sound of a human voice from that of a violin, a handwritten numeral "2" from an "6", one type of fish from another and the aroma of a rose from that of an onion. Hence, PR is nearly everywhere in our life. However, it is difficult for a programmable computer to solve these kinds of perceptual problems. These problems are difficult because each pattern usually contains a large amount of information and the recognition problems typically have an inconspicuous, high-dimensional complex structure. PC is one of important step, in PR, in which the input data object is assigned to one of the given classes. Hence we will focus on designing of state-of-art rule extraction algorithms for PC using soft computing tools.

7. Proposed work plan/Formulation and structure of study:

- **Year-wise plan of work and targets to be achieved**

Year	**Plan**
1	Literature survey and basic implementation
2	Development of novel algorithms, their implementation and result formulation
3	Paper writing and publishing
4	Thesis writing

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